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Predicting Liver Transplant Capacity Using Discrete Event Simulation

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Abstract

The number of liver transplants (LTs) performed in the US increased until 2006, but has since declined despite an ongoing increase in demand. This decline may be due in part to decreased donor liver quality and increasing discard of poor quality livers. We constructed a Discrete Event Simulation (DES) model informed by current donor characteristics to predict future LT trends through the year 2030. The data source for our model is the United Network for Organ Sharing database, which contains patient level information on all organ transplants performed in the US. Previous analysis showed that liver discard is increasing and that discarded organs are more often from donors who are older, obese, have diabetes, and donated after cardiac death. Given that the prevalence of these factors is increasing, the DES model quantifies the reduction in the number of LTs performed through 2030. In addition, the model estimates the total number of future donors needed to maintain the current volume of LTs, and the effect of a hypothetical scenario of improved reperfusion technology. We also forecast the number of patients on the waiting list and compare this to the estimated number of LTs to illustrate the impact that decreased LTs will have on patients needing transplants. By altering assumptions about the future donor pool, this model can be used to develop policy interventions to prevent a further decline in this life saving therapy. To our knowledge, there are no similar predictive models of future LT use based on epidemiologic trends.

Introduction

Liver cirrhosis, which can result in end stage liver disease and hepatocellular carcinoma, is the twelfth leading cause of death in the US [1]. The only cure for cirrhosis is liver transplantation (LT), which offers patients a 5 year survival rate of 74% [2]. Advances in transplantation medicine in the early 1980s transformed LT from an experimental procedure to a standard therapy for end stage liver disease [3], and since that time, continued improvements in management and outcomes have contributed to an expanding volume of

LTs nationally, except in the last decade, where despite an increase in the number of donated livers, the number if transplants has slightly declined due to an increase in non use [2].

Despite the increasing number of transplants in the US in the last few decades, demand has always exceeded supply. Efforts have been made to increase the donor pool by altering procurement strategies to encourage extended criteria donors, including older donors, donors with fatty livers, and organ donation after cardiac death (DCD) [4]. In DCD, organs are procured after donor circulation ceases, in contrast to standard donation after brain death (DBD), where circulation and oxygenation are supported until the time of procurement. The problem with these extended criteria donors is that LT outcomes are generally worse for recipients of these organs as compared to standard donors (i.e. extended criteria donor livers are often considered poor quality organs) [5,6]. Transplant centers are therefore hesitant to use livers from donors with advancing age, diabetes, obesity, and DCD, even when the donors' other organs (e.g. kidney or pancreas) are successfully transplanted [7, 8].

Patients that require a liver transplant are assigned a Model for End Stage Liver Disease (MELD) score based on standard blood work (bilirubin, creatinine and INR), that indicates their priority on the waiting list. Wait lists are stratified by ABO blood type. A donor liver is offered first to the candidate who matches on common elements, such as blood type and body size, and has the highest MELD score (indicating most need). Factors that are important for kidney transplants, such as negative lymphocytotoxic crossmatch and the number of HLA antigens in common between the donor and the recipient, are a non issue for livers. Geographic factors are also taken into consideration; however, while ideally, liver grafts are transplanted within 8 hours, they can remain outside the body for 12 to 15 hours, and thus, can travel farther than heart and lung grafts. Thus, in current practice, if the primary transplant center turns down the donated liver, several other centers will be offered the organ; as such, wastage of donated livers is rare. Moreover, since the number of patients on the waitlist for livers outnumbers the number of donors, the recipients of donated livers are not the limiting factor. Therefore, in this work we focus on the donor liver organs and assume that any offered high quality livers would find a donor. However, to show the impact of decreased liver utilization, we also forecast the waiting list size and show the gap between the waiting list, livers available for transplant, and livers used.

Despite a relatively constant supply of donated livers, the number of transplants performed annually in the US has slightly declined since 2006, and decreased donor liver quality may be partly responsible. Changing donor characteristics reflecting population wide increases in diabetes and obesity along with an emphasis on DCD may have had a deleterious impact on the overall number of LTs performed because of increased discard of such organs. Knowledge of current donor demographic trends and factors associated with liver discard can be used to predict future trends in LT. Such forecasting will aid in developing public health policies and programs oriented towards ensuring availability of and access to this life saving therapy. To date, forecasting of future liver donor quality and its impact on LT volume has not been attempted in the medical literature. Furthermore, forecasting tools commonly used in the medical literature, such as Markov and decision tree modeling, are imprecise when there are multiple variables that influence outcomes changing over time.

Methods

Data and Overall Approach

The United Network for Organ Sharing (UNOS) database contains extensive patient level data on all LTs performed in the US. Data extracted from UNOS and processed through the use of different statistical tools were used to inform a discrete event simulation (DES) model [9] predicting future LTs. Although we considered using US Census data for demographic trends, we found that the UNOS database better represents the population of interest: potential organ donors. That is, the UNOS database better represented key health and demographic attributes of the organ donor population and these factors (age, race, etc.) and the relationships among them were found to be markedly different from other data sources including the Census, National Health and Nutrition Examination Survey (NHANES), and Behavioral Risk Factor Surveillance System (BRFSS). The model was developed utilizing data from 2004 to 2009, with forecasts over the period 2010 2030. Years 2010 and 2011 were reserved for validation. We began by forecasting demographic trends (age, gender, race) accounting for possible correlations. Then we identified factors associated with discard of donated livers using multivariable logistic regression analysis. Incorporating the strengths of these associations and the changing prevalence of these factors over time, we constructed a DES model to estimate future LT utilization. DES enables the tracking of hypothetical individuals moving through a model while concurrently considering changing demographic and health attributes over time [10].

Inclusion/Exclusion Criteria

In our statistical analysis of the data used to parameterize the DES model, we only include donors who had at least one solid organ used for transplant, hence analyzing only those donors who met a minimal threshold for organ donation in general (e.g. HIV negative). Additionally, only donors at least 18 years of age were included. Living donors and split liver donors (where the donated liver is split between two recipients) were excluded because these donors make up a very small proportion of donors and their characteristics are very different from the general donor population. Another reason to exclude these donors is that their liver utilization is 100% as living donations are directed donations to an individual (usually a family member) and split donations are organs of high quality usually split between two children. Donors with a recorded BMI < 14 or > 50 kg/m^2 were also excluded, as these extreme values may be reflective of data entry error in the UNOS database. These criteria are consistent with our previous work on LT trends [8].

The statistical analysis is restricted to time points between 2004 and 2009 and was inclusive of 37, 778 records. While most variables were available since 1995, with varying degrees of completeness, we chose to base our model on records from 2004 onward based on our interest in recent trends [8] and on the completeness of the data. In particular, alcohol consumption was not systematically recorded before this time. However, from 2004 onward, each individual variable of interest was missing for <3% of records.

Statistical Analyses

Independent variables of interest in our logistic regression model included age, obesity (BMI $\geq 30\ kg/m^2$) diabetes, and DCD. Additional covariates included sex, race and alcohol consumption. The primary outcome of interest was a variable indicating whether or not the donated liver was used for a transplant. The Likelihood Ratio Test (LRT) [11] was used to check whether adding higher order interactions caused significant differences in the explanatory power of the logistic regression model. A simpler model was always preferred unless it failed the LRT. All statistical processing was done in R (version 2.15.3). Records with missing variables were eliminated from the analysis. About 3% of records were excluded due to missing variables. Additional details related to the regression models can be found in the appendices.

Table 1 presents an overview of the parameters used by the simulation model with additional details about the methods by which these variables were generated (i.e., relationships with independent variables and statistical models). These model parameters were selected based on a retrospective analysis of risk factors for liver discard [8].

Demographic Variables—We analyzed historical demographic trends in the gender, race and age of donors in the UNOS database. Our analysis revealed that the proportion of men and women in the donor pool has been stable, with the percentage of men being higher, accounting for 59% of the donors. Using this information, an empirical discrete probability distribution was used to generate the gender of hypothetical individuals moving through the simulation model, mirroring historical trends. Our analysis revealed that age, gender and race were interrelated; therefore, our analytic and simulation models incorporated stratification to appropriately represent this interdependence of important demographic variables influencing donation. We have included data from donors reported in UNOS as being non Hispanic white, non Hispanic black or Hispanic, with other races (accounting for 2% of donors) excluded. Race was reported by the local organ procurement organization, which is the entity that coordinates the organ donation process. The percentage of donors belonging to each race category was generated using linear regression models stratified by gender. Following previous work [8], we specified age groups categorically (<30, 30 39, 40 49, 50 59, and ≥60 years). The probability distribution of age categories is calculated using ordinary Least Squares Linear Regression models with stratification by gender and race. That is, using the regression, we predict the proportion of simulated individuals in each age category, with the age category ≥60 as the referent group; such that the proportion of donors in category ≥60 is 1minus the sum of the proportion of donors in all other age categories. These proportions then define a discrete distribution from which we draw a donor's age category. This is similarly done for race, where Hispanic is used as the referent race category. We considered other model specification methods to project gender, race, and age (such as moving average and single exponential smoothing); however, linear regression models were selected in every case either because the forecasting error was the smallest or because, statistically, linear regression yielded predictions equivalent to those from alternate models, and the linear regression model was simpler.

Obesity—The UNOS database contains the *BMI* of each donor. As a risk factor for liver discard, we modeled whether a patient is obese (BMI > 30kg/m^2) or not as a dichotomous variable. We tested alternate functional forms of BMI, but the use of a continuous variable or a more complex categorical variable did not substantially improve the predictive value. Because obesity prevalence has increased over time, the likelihood of being obese was estimated using a multivariable logistic regression that depends on the demographic attributes of the donor as well as on time (Table 1).

Alcohol consumption is reported in the UNOS database as a Yes/No variable (Yes, if ≥ 2 drinks per day). Although preliminary analysis showed that the overall alcohol consumption at the population level has been stable over the time period of analysis, alcohol consumption does depend upon demographic attributes, which are changing over time. Accordingly, a multivariable logistic regression model was used to predict alcohol consumption based upon the demographic attributes of the donor population.

Cause of Death—Livers of donors who die of stroke pose an increased risk for liver graft failure after transplant, and are more likely to be discarded compared to other causes of death [6, 8]. We originally estimated *stroke* prevalence as a function of demographic attributes, time, diabetes, and obesity. However, in preliminary analyses, stroke prevalence was not correlated with diabetes or obesity, so the final logistic regression predicting stroke was modeled as a function of demographic attributes and time only. While stroke incidence may be correlated to diabetes or obesity in the general population, it is not necessarily the case in a successful donor population, which is our population of interest.

Donation after Cardiac Death (DCD) has increased over the last six years as a strategy to procure more organs [9]. Thus, the rising trend of DCD was projected by using a linear regression model dependent only on time.

Serum bilirubin is a marker of liver dysfunction, and is categorized as ≤1.2, 1.3 2.5, 2.6 5.0 and >5.0 *mg/dL*, with higher values indicative of worse function. Elevated levels of bilirubin among organ donors are typically related to acute illness at the end of life and are not generally related to other clinical attributes. Accordingly, the percentage of donors in each serum bilirubin category has been stable over time, and these percentages are not related to demographic attributes. The serum bilirubin projection was the done by using an empiric discrete probability distribution.

Alanine Aminotransferase levels (ALT) are also reflective of liver damage, with mild moderate elevations characteristic of stable chronic liver disease (often fatty liver) and more severe elevations indicative of acute illness (as with elevated bilirubin). These levels were categorized as follows: ≤40, 41 200, 201 400 and >400 U/L. Because the causes of elevated ALT differ with respect to the magnitude of the elevation, nested logistic regression models were used to forecast ALT. Initially the data were divided into two categories ≤40 and >40, and a logistic regression was used to predict the likelihood of being in the ≤40 category. Then, among those patients in the category>40, a new logistic regression model was fitted to predict the likelihood of being in the 41 200 category. Finally, two subsequent logistic regressions were used to predict the likelihood of being in the categories 201 400 and >400.

Each of these models was estimated as a function of demographic attributes and time: the first model has Age, Obesity, Diabetes and Year as independent variables; the second has Age and Year and the third has Age, Diabetes and Year.

Finally, *liver nonuse* was defined as a liver procured from an organ donor that was not transplanted into a recipient. A logistic regression model depending on the remaining variables was used to predict whether or not a donated liver would be used for transplantation.

Simulation Model

Figure 1 shows how variables are linked in the simulation model. The boxes indicate the model variables, directional arrows indicate dependencies between variables, and the gray shading indicates that a variable also depends on time (or model year). The model was implemented using the software Arena version 15 (Rockwell Automation). We use the simulation model to forecast the future availability of livers for transplantation, as well as the probability of those livers being utilized. Since the forecast is simulation based, it incorporates uncertainties related to key demographic factors as well as health attributes and conditions that have been associated with organ donation and organ quality. The simulation also takes into account the correlation found among several variables. This is done by carefully generating the variables in the order suggested by the flow diagram (Figure 1) so that dependencies can be observed and explicitly modeled. The simulation model allows individual specific, as opposed to cohort or population based, simulation, which incorporates the multiple complex permutations of individual demographic and health attributes with the final goal of estimating the number of livers effectively available for and used in transplantation over the long term.

The simulation is performed by running 15 replications, each one simulating 100,000 patients. This number of patients was sufficient to capture the heterogeneity of the donor population as well as observe low probability events. This number of replications allowed us to achieve a 95% confidence interval half width of 1% or less about our estimate of utilization for all years. The confidence intervals describe the reliability of our estimate. The accuracy of our results with respect to how well they predict the actual trends is described in the Validation Section of the Results.

The Waiting List

To show the impact that the decreased number of LTs would have, it is also important to consider the number of patients waiting for a transplant. To forecast the waiting list we use data from the Organ Procurement and Transplantation Network (OPTN) (http://optn.transplant.hrsa.gov). OPTN provides the number on the waiting list at a specific point in time, the number of additions to the waiting list, by year, as well as the number of removals from the waiting list, by year and cause. We focus on adult (18 years of age and over) candidates. We note that candidates are different from registrations. A patient who is waiting at more than one center or for multiple organs would be considered a single candidate, where as a patient who is waiting at more than one center or for multiple organs would have multiple registrations. On January 31, 2014, there were 15, 267 adult patients on

the waiting list. We estimate the number of patients prior to 2014 using the following equation, number of waiting list candidates in year *i+1*= number of waiting list candidates in year *i* + number of candidates added in year *i* number of candidates removed in year *i*. Removal from all causes is considered (deceased or live donor transplant, deceased, transplant in another country, etc.). To forecast the waiting list size we use ordinary least squares regression with the independent variable year. To be consistent with the simulated variables, we use the estimated waitlist size from 2004 to 2009 to fit the model; since we were are to query the waitlist at a later date through the OPTN website, we can compare our model fit with historical data through 2014.

Study Design (Scenarios)

Several potential scenarios were defined and analyzed. Scenario I assumes that all trends projected by the model will continue for the 20 year period. However, some studies have suggested that the increase in obesity for adults in the US appears to have stagnated [12]. We therefore defined Scenario II in which we suppressed the effect of time after the year 2020 for all those parameters for which time was a significant predictor, except for the demographic parameters. For instance, in the simulation model, obesity and diabetes depend on time, but after 2020, the 'year' variable was held constant at the 2020 value. Therefore predictions of obesity and diabetes in the years after 2020 will depend only on time to the extent that demographic trends shift over time.

We then considered an additional plausible scenario that might alter current trends or change the risk of liver discard. Scenario III considers an improvement in organ reperfusion technology, which could improve the quality of organs previously considered unsuitable for transplant [13-16]. Such improvements may mitigate the risk of using fatty livers or DCD livers and therefore increase the utility of such livers [13]. Assuming a reperfusion technology that becomes available in 2015 and is incorporated into clinical practice with an S shaped diffusion of innovation curve [17], and estimating between a 5 to 20% (according to a triangular distribution with mode 10%) associated reduction in the risk of liver discard for (IIIa) diabetic *and* obese donors, (IIIb) diabetic *or* obese donors, and (IIIc) DCD donors, we created a new forecast.

In this simulation model, we are required to make assumptions about the expected number of donors in the future. Two possibilities are considered. Based on historical data, from 2006 onward the annual number of adult organ donors meeting our inclusion and exclusion criteria has remained relatively constant (around 6,500 donors/year). In the first case, we therefore assume that this trend will continue, and this number is held constant. As an alternate possibility, we consider an optimistic 3% annual increase in the number of donors after 2010.

To show the gap between supply and demand for LTs, we also show our forecast for the number of patients on the waiting list. Here again, two possibilities are considered, one in which the number of the waiting list continues to increase, and one in which the number of candidate on the waiting list remains constant after 2014.

This study was exempt from review by the University of North Carolina Institutional Review Board because it used de identified publically available data (Study # 11 1948).

Results

Validation

Figure 2 illustrates simulated trends for several key variables from years 2004 to 2011, overlaid with the historical values for comparison. Recall that years 2010 and 2011 were not used in any of the predictive regression models as they were reserved for validation. Overall, for each one of the variables being forecasted by the simulation model the estimation error was within 1% of the actual historical data. Trends for all variables, simulated and historical, are provided in the Appendix. In terms of our forecast of the waiting list, Figure 3 shows waiting list candidates from years 2004 to 2014, where the years 2010 through 2014 were withheld from the model.

Figure 4 shows the trends in the donor population from 2010 to 2030 for the base scenario (Scenario I). Over that 20 year period the proportion of donors over the age of 50 will increase from 39% to 44% the prevalence of diabetes among organ donors will increase from 14% to 46%, and the prevalence of obesity will increase from 31% to 58%.

Figures 5 and 6 show the results for scenarios I and II respectively under the two assumptions for the number of donors in panels (a), the donors remain constant, in panels (b) the donors increase by 3% annually. From Figure 5(a) we can see that if the number of donors stays at its current level and the trends in all the input parameters continue as before (Scenario I), then there will be a continuous decline in the number of LTs. This would be the result of a stagnated pool of donors as well as an increasing prevalence of factors associated with nonuse, such as older age, obesity, diabetes, and DCD. Figure 5(b) shows that in order to maintain the current LT volume, the number of liver donors would need to increase by at least 3% per year. However, even with that increase in the number of donors we can see a declining trend in LT after 2025. In other words, the deterioration of liver quality will eventually surpass the assumed increase in the number of donors.

Figure 6 corresponds to the scenario in which we suppress the effect of time after the year 2020 in our projections (Scenario II). The same alternative assumptions about the number of donors are considered: one case in which the number of donors is held constant at 6,500/year (panel (a)) and one case in which the number of donors will increase by 3% per year (panel (b)). Under the assumption of a constant number of donors, we can see that after 2020 LTs would continue to decrease, though at a much slower rate, there is only a loss of 58 LTs between 2020 and 2030. For the alternative assumption of an increasing number of donors, LTs will increase after 2020. Even then, however, the slope of the increase in LT is smaller than the slope of the increase in number of donors. In other words, there would still be deteriorating quality of donated livers, which will lead to increased discard rates.

In Scenario III we performed a simulation where a hypothetical change in organ reperfusion technology was implemented in 2015 over the course of 10 years according to a diffusion curve. In the base case, in which the donor pool remained constant, the rate of discard

among population of donors who were either obese or diabetic was 60.2% (in 2030). When advances in reperfusion affect only donors who are both obese and diabetic (Scenario IIIa), this rate of discard is reduced to 57.0%; while if the technique affects either obese or diabetic donors (Scenario IIIb), the rate of discard is reduced to 53.1%. The rate of discard among DCD donors is reduced from 82.5% to 75.2% if the reperfusion technique is applied to DCD livers (Scenario IIIc). Overall, donor utilization was increased by 2.4% to 46.0% by 2030 when reperfusion techniques were applied to donors with both diabetes *and* obesity. Utilization was increased by 5.2% to 48.8% by 2030 if the technology benefitted patients with either diabetes *or* obesity. Utilization increased by 3.5% to 47.1% by 2030 when new reperfusion technology reduced the risk of DCD liver discard. The results are shown in Figure 7, for the base case, in which the donor pool remains constant, all three versions of the technology effect are shown with our original predictions also shown as “no change”.

Lastly, we forecast the waitlist size, and again consider two cases. In one case (panel (a)), the wait list size stays constant after 2014, in the other case (panel (b)) it continues to increase as per our forecast. Figure 8 shows the gap between supply and demand (wait list minus LTs) assuming the donor pool remains constant for scenarios I, II, and III (c).

Discussion

A decreasing trend in the number of livers being transplanted has been observed previously [8]. Given the importance of LT as an option to save lives, this decreasing trend generates concerns about the ability of current liver donation processes to meet future demand. In this context, we modeled the current system and forecasted future supply and non use of livers to better inform decision making about policies that may be implemented to improve donation outcomes and reduce waitlist size. Several variables affect the final decision of using or discarding a donated liver, including: demographic attributes, clinical risk factors, epidemiologic factors and comorbidities. To identify which factors are most relevant to the decline in liver use, and which are most modifiable, we develop a DES model that captures these complexities by allowing for interrelationships among variables to exist over time.

Our analyses indicate that observed trends in donor characteristics are expected to result in further declines in LTs in 5, 10, and 20 years. One strength of our approach is that DES modeling allows us to estimate these changes with precision. Furthermore, the DES model allows us to estimate how many additional donors will need to be recruited to maintain current LT levels. Our forecast of the waiting list size allows us to estimate the gap between supply and demand for livers. Such information can be critical to helping design policies to sustain or augment the number and quality of livers available for transplant. DES also allows for creating and evaluating “what if” scenarios. Since we are including the modeling of each input parameter as a separate module, it is possible to evaluate the effect of possible changes on a particular variable (or several of them, probably interrelated), as a result of changes in policies, procedures or technologies, for instance. This can be useful to inform policy makers about alternative ways to improve the utilization of donated livers. One such example was provided in Scenario III, where we considered the hypothetical scenario of improved reperfusion technology. Results show that such improvements, as optimistic as they are, can only reduce the rate of discard by about 5%. Thus, the total utilization rate will

still remain lower than current levels despite these optimistic assumptions. This model can be used in future studies to help influence donation and procurement policies in the context of increasing rates of metabolic disease and consequent liver discard. That is, it can help us to quantify the effectiveness of policy changes with respect to existing procurement strategies, such as extended criteria donation. Regarding future trends in the underlying donor population, the current model makes assumptions about the expected number of donors available in the future and the composition of the donor population. While we consider changes in the aggregate number (constant versus an annual 3% increase, obesity increases versus stagnates) the current model does not incorporate a detailed forecast of the entire donor pool, i.e. those patients/families that decline organ donation. One way to incorporate a detailed model of the supply of liver donations would be to use the census population and mortality rates for different demographics (such as age and race) jointly with a model for either likelihood of donation, based on historical rates of donation by strata, or a model for "willingness to donate" which considers that drivers of donation (such as patient demographics, religious beliefs and state level opt in policies) may change over time. However, we suspect that this forecast for liver graft availability may be rendered even more pessimistic if demographic shifts in the U.S. trend toward populations that have historically low organ donation rates [18]. While it is outside the scope of this research, as future work, we would like to expand the model so that it can also be used to quantify changes in policies that improve organ donation.

DES is a strong methodological approach over other commonly used models, such as Markov processes. By using DES we were able to employ different statistical processing tools for each relevant input parameter, selecting in each case the statistical tool that better suited the forecast of each variable. DES models have been used in the past in relation to liver transplantation. In [19] the authors developed a DES framework to model the US liver allocation system incorporating the stochastic disease specific natural history of patients. They mentioned that their model could be used for estimating the number of transplants performed as well as the number of wasted livers, among other statistics of interest. In [10] the authors also used DES to build a biologically based model of liver transplantation so that changes in allocation policies could be evaluated. The work in [20] describes a family of simulations developed by the *US Scientific Registry of Transplant Recipients*, used to predict the likely effects of different allocation policies. In [21] they used a multistage Markov decision analysis model to analyze the survival chances under different treatments of patients requiring liver transplantation. The authors mention that although many problems can be modeled by Markov Decision Process (MDP), when the number of states is too large or the system is complex enough so that MDP's parameters become hard to estimate, simulation becomes a valid alternative with high precision and reasonable computation time. We are using DES, taking advantage of its ability to deal with a system in which there are complex relationships among key variables. Furthermore, unlike the works mentioned we are not modeling the allocation policies. Instead we are interested in predicting the availability of livers and their quality. The allocation process is a step further once a suitable liver becomes available. We have not found previous research attempting to analyze the future availability of livers for transplantation, taking into account the explanatory factors of the quality of the livers being donated.

A number of limitations accompany our analyses. For example, not all available variables were included in the analysis (e.g. self reported drug use); adding these variables could enhance the predictive power of the model; however there are concerns about reliability of variables such as drug use due to inherent bias in self report. In addition, some of the variables that we used were categorized to facilitate the analysis, which has been a common practice in previous research. However it may be the case that keeping all the information from the variables can improve the accuracy of the forecast. As with any forecast, this is an extrapolation into the future, which is unknown. While we have shown that the model adequately predicted the years 2010 and 2011, its accuracy beyond that is unknown. Major shifts in demographic and clinical factors in the population, as well as major shifts in technology could impact utilization. We have tried to take this into account to the extent possible by considering hypothetical scenarios, such as changes in obesity trends and changes in organ reperfusion technology. Lastly, as previously discussed, the current model does not include a detailed forecast of those patients/families that decline organ donation.

In conclusion, this work is the first to forecast liver's availability and quality at the US population level with high level of accuracy. Results show that if current trends continue this could result in 2230 (44%) fewer LTs by 2030. In order to maintain the number of LTs from 2010, despite these trends, 5115 additional organ donors will be needed in 2030. Furthermore, if waitlist size continues to grow at the same rate, there will be 12429 candidates on the list in 2030 who do not receive a liver. This grim outcome cannot be mitigated alone by even radical technological advances, a stabilization of negative clinical attributes (such as obesity) or an increase in the donor population. Likely, a combination of strategies that increase donor pool, improve donor liver quality, and make better use of inferior quality livers, will be necessary to keep up with LT demand. Unless the transplant community develops improved strategies for organ allocation and utilization, the only way to maintain the number of LTs at the current levels may be to accept inferior grafts at the risk worse post transplant outcomes.

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Appendix

Simulation Model Implementation Details

Below are the distributions used in the model for each independent variable.

Gender

Discrete distribution, 41.3% female, 58.7% male

Age

Age category is assigned according to a discrete distribution that changes over time and depends on gender. The probability that age category x is assigned in year is given by $P(x,y)= \alpha(x)+\beta y$ for x={<30, 30-39, 40-49, 50-59}. $P(60, y)= 1-\Sigma_{x<60} P(x,y)$. In these equations "α"s are given by the "Intercept" estimates and "β"s are given by the "Year" estimates shown in the Regression Details Section of the Appendix.

Race

Race category is assigned according to a Discrete distribution that changes over time and depends on gender. The probability that Race category x is assigned in year is given by $P(x,y)= \alpha(x)+\beta y$ for x={White, Black}. $P(Hispanic, y)= 1-\Sigma_{x<60} P(x,y)$. In these equations "α"s are given by the "Intercept" estimates and "β"s are given by the "Year" estimates shown in the Regression Details Section of the Appendix.

The variables **BMI, Alcohol, Diabetes, Stroke, and Use** are modeled using logistic regressions. Where we obtain P(Y) using P(Y)= e^(Y)/[1+e^Y]; $Y= \beta_0+-\Sigma_j \beta_j$. β_0 corresponds to intercept estimates and β_js correspond to the estimates for each of the dependent variables listed in the Regression Details Section of the Appendix. Then P(Y) is used to sample from a discrete distribution with a binary outcome, yes or no.

Bilirubin

Discrete distribution categorized as ≤ 1.2, 1.3-2.5, 2.6 -5.0 and >5.0 *mg/dL* with the respective probabilities: 73.7%, 21.0%, and 4.0% and 1.3%

DCD

Assigned according to a discrete distribution that changes over time. The probability the organ comes from a DCD donor in year is given by $P(y)= \alpha+\beta y$ where "α" is given by the "Intercept" estimate and "β" is given by the "Year" estimate shown in the Regression Details Section of the Appendix.

ALT

First, we divide the data into two categories, ≤40 and >40, and a logistic regression was used to predict the likelihood of being in the ≤40 category. Then, among those patients in the category>40, a new logistic regression model was fitted to predict the likelihood of being in the 41-200 category. Finally, two subsequent logistic regressions were used to predict the likelihood of being in the categories 201-400 and >400. The probabililities of being in each of the binary categories at each step is calculated as explained for the other variables using logistic regression above. Then, we use conditional probabilities to obtain the probabilities of being in each of the original 4 categories. That is Pr(≤40) is given right away, as the first regression provides Pr(≤40) and Pr(>40)=1- Pr(≤40). Then Pr(41-200)= Pr(41-200| >40)xPr(>40). This is repeated for the other categories.

Waitlist

Waitlist size Y follows a linear regression where $Y=\alpha+\beta y$. In this case y is the current year, such as 2004.

Regression Models Details

Male - Age <30

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.307051	0.007361	41.714	3.03e-05
Year	-0.004563	0.003005	-1.519	0.226

Residual standard error: 0.009503

Multiple R-squared: 0.4346, Adjusted R-squared: 0.2461, p-value: 0.2262

Male - Age 30-39

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	1.521e-01	2.559e-03	59.438	1.05e-05
Year	4.096e-05	1.045e-03	0.039	0.971

Residual standard error: 0.003303

Multiple R-squared: 0.0005123, Adjusted R-squared: -0.3327, p-value: 0.9712

Male - Age 40-49

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.2126201	0.0047586	44.68	2.47e-05
Year	-0.0007567	0.0019427	-0.39	0.723

Residual standard error: 0.006143

Multiple R-squared: 0.04814, Adjusted R-squared: -0.2691, p-value: 0.7229

Male - Age 50-59

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.194718	0.004380	44.457	2.51e-05
Year	0.004403	0.001788	2.462	0.0907

Residual standard error: 0.005654

Multiple R-squared: 0.6689, Adjusted R-squared: 0.5586, p-value: 0.0907

Male - Age >60

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.1335192	0.0048541	27.506	0.000105
Year	0.0008765	0.0019817	0.442	0.688207

Residual standard error: 0.006267

Multiple R-squared: 0.06122, Adjusted R-squared: -0.2517, p-value: 0.6882

Female - Age <30

Coefficients:

	Estimate	Std. Error	t value	Pr(> |t|)
(Intercept)	0.158056	0.005804	27.233	0.000109
Year	0.002390	0.002369	1.009	0.387421

Residual standard error: 0.007493

Multiple R-squared: 0.2533, Adjusted R-squared: 0.00435, p-value: 0.3874

Female - Age 30-39

Coefficients:

	Estimate	Std. Error	t value	Pr(> |t|)
(Intercept)	0.134720	0.008739	15.417	0.000593
Year	-0.000486	0.003567	-0.136	0.900268

Residual standard error: 0.01128

Multiple R-squared: 0.006148, Adjusted R-squared: -0.3251, p-value: 0.9003

Female - Age 40-49

Coefficients:

	Estimate	Std. Error	t value	Pr(> |t|)
(Intercept)	0.248626	0.007147	34.788	5.22e-05
Year	0.000337	0.002918	0.116	0.915

Residual standard error: 0.009227

Multiple R-squared: 0.004427, Adjusted R-squared: -0.3274, p-value: 0.9153

Female - Age 50-59

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.246048	0.005810	42.347	2.9e-05

Year	0.003255	0.002372	1.372	0.264

Residual standard error: 0.007501

Multiple R-squared: 0.3856, Adjusted R-squared: 0.1808, p-value: 0.2636

Female - Age >60

Coefficients:

	Estimate	Std. Error	t value	Pr(> 111)
(Intercept)	0.212550	0.006124	34.706	5.26e-05
Year	-0.005494	0.002500	-2.197	0.115

Residual standard error: 0.007906

Multiple R-squared: 0.6168, Adjusted R-squared: 0.4891, p-value: 0.1155

Male - Race White

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.747167	0.007111	105.071	7.52e-14
Year	-0.008250	0.001332	-6.194	0.000261

Residual standard error: 0.0121

Multiple R-squared: 0.8275, Adjusted R-squared: 0.8059, p-value: 0.0002612

Male - Race Black

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.1222422	0.0026032	46.959	4.68e-ll
Year	0.0042008	0.0004876	8.615	2.55e-05

Residual standard error: 0.004429

Multiple R-squared: 0.9027, Adjusted R-squared: 0.8905, p-value: 2.553e-05

Male - Race Hispanic

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.130590	0.005766	22.65	1.53e-08
Year	0.004050	0.001080	3.75	0.00563

Residual standard error: 0.00981

Multiple R-squared: 0.6374, Adjusted R-squared: 0.592, p-value: 0.005625

Female - Race White

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.799906	0.005799	137.946	8.53e-15
Year	-0.009455	0.001086	-8.705	2.37e-05

Residual standard error: 0.009866

Multiple R-squared: 0.9045, Adjusted R-squared: 0.8926, p-value: 2.367e-05

Female - Race Black

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.102636	0.005867	17.493	1.16e-07
Year	0.007446	0.001099	6.775	0.000141

Residual standard error: 0.009982

Multiple R-squared: 0.8516, Adjusted R-squared: 0.833, p-value: 0.0001414

Female - Race Hispanic

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0974578	0.0040719	23.934	9.89e-09
Year	0.0020092	0.0007627	2.634	0.03

Residual standard error: 0.006928

Multiple R-squared: 0.4645, Adjusted R-squared: 0.3975, p-value: 0.02999

BMI

Coefficients:

	Estimate	Std. Error	z value	Pr(> | z |)
(Intercept)	-87.366924	19.148313	-4.563	5.05e-06
GenderM	-1.109458	0.126132	-8.796	< 2e-16
Age>=60	0.237314	0.136855	1.734	0.082909
Age30-39	0.270857	0.140752	1.924	0.054310
Age40-49	0.341998	0.122704	2.787	0.005317
Age50-59	0.422617	0.124174	3.403	0.000665
RaceHispanic	2.439582	27.969924	0.087	0.930495
RaceWhite	-51.064656	20.915100	-2.442	0.014626
year	0.043198	0.009547	4.525	6.05e-06
GenderM :Age>=60	0.331250	0.188505	1.757	0.078875
GenderM :Age30-39	0.687985	0.179629	3.830	0.000128

GenderM :Age40-49	0.498453	0.160411	3.107	0.001888
GenderM:Age50-59	0.170108	0.165596	1.027	0.304305
GenderM:RaceHispanic	0.721618	0.179217	4.026	5.66e-05
GenderM:RaceWhite	0.691696	0.140777	4.913	8.95e-07
Age>=60:RaceHispanic	0.242861	0.208022	1.167	0.243017
Age30-39:RaceHispanic	0.443973	0.205978	2.155	0.031127
Age40-49:RaceHispanic	0.346030	0.186828	1.852	0.064007
Age50-59:RaceHispanic	0.439398	0.188255	2.334	0.019593
Age>=60:RaceWhite	0.164633	0.150857	1.091	0.275133
Age30-39: RaceWhite	0.264082	0.156605	1.686	0.091740
Age40-49: RaceWhite	0.235071	0.136988	1.716	0.086162
Age50-59: RaceWhite	0.252462	0.138082	1.828	0.067499
RaceHispanicyear	-0.001532	0.013947	-0.110	0.912520
RaceWhite:year	0.025103	0.010429	2.407	0.016079
GenderM:Age>=60:RaceHispanic	-0.524963	0.281716	-1.863	0.062399
GenderM:Age30-39:RaceHispanic	-0.861232	0.255950	-3.365	0.000766
GenderM:Age40-49:RaceHispanic	-0.429464	0.235367	-1.825	0.068053
GenderM:Age50-59:RaceHispanic	-0.200124	0.241284	-0.829	0.406872
GenderM:Age>=60:RaceWhite	0.149804	0.206032	0.727	0.467171
GenderM:Age30-39:RaceWhite	-0.519040	0.200004	-2.595	0.009455
GenderM:Age40-49:RaceWhite	-0.155751	0.178376	-0.873	0.382576
GenderM:Age50-59:RaceWhite	0.217655	0.182938	1.190	0.234133

Null deviance: 2110.55 on 299 degrees of freedom

Residual deviance: 284.23 on 267 degrees of freedom

AIC: 1825.1

Alcohol

Coefficients:

	Estimate	Std. Error	z value	Pr(> | z |)
(Intercept)	-3.46135	0.16378	-21.134	< 2e-16
GenderM	0.93232	0.13353	6.982	2.91e-12
Age>=60	0.72548	0.19842	3.656	0.000256
Age30-39	1.26358	0.18671	6.768	1.31e-ll
Age40-49	1.68070	0.16647	10.096	< 2e-16
Age50-59	1.37501	0.16928	8.123	4.56e-16
RaceHispa	-0.08106	0.19433	-0.417	0.676593
RaceWhite	0.81997	0.14770	5.551	2.83e-08
GenderM :Age>=60	0.18205	0.13324	1.366	0.171843
GenderM :Age30-39	-0.03443	0.12959	-0.266	0.790461
GenderM :Age40-49	-0.07111	0.11535	-0.616	0.537600
GenderM:Age50-59	0.15922	0.11763	1.354	0.175880
GenderM:RaceHispa	0.47804	0.14217	3.362	0.000773

GenderM:RaceWhite	-0.05577	0.09621	-0.580	0.562159
Age>=60:RaceHispa	-0.17169	0.23113	-0.743	0.457584
Age30-39:RaceHispa	-0.18022	0.19864	-0.907	0.364254
Age40-49: RaceHispa	-0.28060	0.18167	-1.545	0.122458
Age50-59:RaceHispa	-0.25913	0.18676	-1.387	0.165294
Age>=60:RaceWhite	-0.54777	0.17752	-3.086	0.002030
Age30-39: RaceWhite	-0.40926	0.16368	-2.500	0.012406
Age40-49: RaceWhite	-0.50664	0.14544	-3.484	0.000495
Age50-59: RaceWhite	-0.52747	0.14739	-3.579	0.000345

Null deviance: 1996.1471 on 29 degrees of freedom

Residual deviance: 2.0629 on 8 degrees of freedom

AIC: 234.8

Diabetes

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-1.888e+02	1.796e+01	-10.509	< 2e-16
GenderM	-1.021e+00	1.326e-01	-7.695	1.41e-14
RaceHispa	4.220e+01	2.644e+01	1.596	0.110435
RaceWhite	4.398e+01	1.971e+01	2.232	0.025625
Age>=60	2.204e+00	1.816e-01	12.137	< 2e-16
Age30-39	8.240e-01	2.040e-01	4.039	5.38e-05
Age40-49	1.336e+00	1.811e-01	7.378	1.61e-13
Age50-59	1.817e+00	1.783e-01	10.189	< 2e-16
Year	9.237e-02	8.960e-03	10.309	< 2e-16
ObeseY	7.966e-01	2.898e-02	27.489	< 2e-16
GenderM: RaceHispa	-3.656e-02	9.998e-02	-0.366	0.714580
GenderM: RaceWhite	1.731e-01	7.530e-02	2.299	0.021487
GenderM:Age>=60	1.374e+00	1.276e-01	10.769	< 2e-16
GenderM:Age30-39	6.743e-01	1.482e-01	4.549	5.38e-06
GenderM :Age40-49	1.028e+00	1.302e-01	7.897	2.85e-15
GenderM:Age50-59	1.129e+00	1.264e-01	8.935	< 2e-16
RaceHispa:Age>=60	-4.825e-02	2.361e-01	-0.204	0.838083
RaceWhite:Age>=60	-8.108e-01	1.847e-01	-4.391	1.13e-05
RaceHispa:Age30-39	-1.528e-01	2.648e-01	-0.577	0.563940
RaceWhite:Age30-39	-4.415e-01	2.086e-01	-2.117	0.034280
RaceHispa:Age40-49	1.441e-01	2.340e-01	0.616	0.538220
RaceWhite:Age40-49	-6.581e-01	1.849e-01	-3.559	0.000372
RaceHispa:Age50-59	5.486e-02	2.310e-01	0.237	0.812287
RaceWhite:Age50-59	-6.323e-01	1.816e-01	-3.482	0.000498
RaceHispa:Year	-2.105e-02	1.319e-02	-1.596	0.110554
RaceWhite:Year	-2.196e-02	9.831e-03	-2.234	0.025498

Null deviance: 42409 on 76898 degrees of freedom

Residual deviance: 37177 on 76873 degrees of freedom

AIC: 37229

DCD

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.0051997	0.0072109	-0.721	0.503
Year	0.0118093	0.0009905	11.923	7.32e-05

Residual standard error: 0.005241

Multiple R-squared: 0.966, Adjusted R-squared: 0.9592, p-value: 7.315e-05

Stroke

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-8.862e-01	1.569e+01	-0.056	0.954965
Age>=60	4.484e+01	1.527e+01	2.938	0.003308
Age30-39	2.764e+01	1.380e+01	2.003	0.045227
Age40-49	6.030e+01	1.296e+01	4.653	3.28e-06
Age50-59	8.523e+01	1.362e+01	6.258	3.89e-10
GenderM	-3.422e+01	7.978e+00	-4.289	1.80e-05
RaceHispa	-4.683e-01	1.676e+01	-0.028	0.977709
RaceWhite	7.619e+01	1.260e+01	6.048	1.47e-09
Year	-1.507e-04	7.834e-03	-0.019	0.984652
Age>=60:GenderM	6.099e-01	6.695e-02	9.109	< 2e-16
Age30-39:GenderM	1.765e-01	6.297e-02	2.803	0.005070
Age40-49:GenderM	3.685e-01	5.863e-02	6.286	3.26e-10
Age50-59:GenderM	4.979e-01	6.099e-02	8.164	3.23e-16
Age>=60:RaceHispa	-5.845e-01	1.355e-01	-4.314	1.60e-05
Age30-39:RaceHispa	-3.238e-01	1.104e-01	-2.932	0.003363
Age40-49: RaceHispa	-5.035e-01	1.055e-01	-4.773	1.81e-06
Age50-59:RaceHispa	-5.203e-01	1.142e-01	-4.556	5.21e-06
Age>=60:RaceWhite	-9.037e-02	1.068e-01	-0.846	0.397635
Age30-39: RaceWhite	-2.354e-01	8.965e-02	-2.626	0.008650
Age40-49: RaceWhite	-4.786e-01	8.435e-02	-5.674	1.40e-08
Age50-59: RaceWhite	-3.388e-01	9.072e-02	-3.734	0.000188
Age>=60:Year	-2.081e-02	7.619e-03	-2.732	0.006302
Age30-39:Year	-1.303e-02	6.891e-03	-1.891	0.058670
Age40-49:Year	-2.882e-02	6.470e-03	-4.455	8.41e-06
Age50-59:Year	-4.106e-02	6.797e-03	-6.041	1.53e-09
GenderM:RaceHispa	2.268e-02	7.255e-02	0.313	0.754560

GenderM: RaceWhite	1.110e-01	5.502e-02	2.017	0.043668
GenderM :Year	1.645e-02	3.983e-03	4.130	3.63e-05
RaceHispa:Year	2.923e-04	8.368e-03	0.035	0.972135
RaceWhite:Year	-3.824e-02	6.289e-03	-6.081	1.20e-09

Null deviance: 27343.4 on 1722 degrees of freedom

Residual deviance: 2167.2 on 1693 degrees of freedom

AIC: 6752.4

ALT - <=40 - >40

Coefficients:

	Estimate	Std. Error	z value	Pr(> | z |)
(Intercept)	66.060988	3.480759	18.979	< 2e-16
AgeCat>=60	0.985003	0.026545	37.107	< 2e-16
AgeCat30-39	0.090342	0.023593	3.829	0.000129
AgeCat40-49	0.274738	0.021614	12.711	< 2e-16
AgeCat50-59	0.509089	0.022732	22.396	< 2e-16
Obese.Y	-0.265279	0.018350	-14.457	< 2e-16
Diabetes.Y	0.132932	0.029767	4.466	7.98e-06
year	-0.032894	0.001738	-18.923	< 2e-16

Null deviance: 2627.2 on 318 degrees of freedom

Residual deviance: 327.8 on 311 degrees of freedom

AIC: 1858.5

ALT - 41-200 - >200

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	70.407817	7.656245	9.196	< 2e-16
AgeCat>=60	0.981491	0.072491	13.539	< 2e-16
AgeCat30-39	0.149785	0.045355	3.302	0.000958
AgeCat40-49	0.397113	0.043958	9.034	< 2e-16
AgeCat50-59	0.669555	0.050792	13.182	< 2e-16
year	-0.034443	0.003822	-9.012	< 2e-16

Null deviance: 740.80 on 314 degrees of freedom

Residual deviance: 332.18 on 309 degrees of freedom

AIC: 1300.8

ALT - 201-400 - >400

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	51.58996	14.12514	3.652	0.000260
AgeCat>=60	0.69847	0.14491	4.820	1.44e-06
AgeCat30-39	0.13017	0.08229	1.582	0.113692
AgeCat40-49	0.21430	0.08094	2.648	0.008107
AgeCat50-59	0.35092	0.09622	3.647	0.000265
Diabetes.Y	0.26195	0.13305	1.969	0.048972
year	-0.02581	0.00705	-3.661	0.000252

Null deviance: 346.95 on 265 degrees of freedom

Residual deviance: 293.42 on 259 degrees of freedom

AIC: 869.3

Liver Usage

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	103.34785	20.16547	5.125	2.98e-07
Age>=60	-0.84203	0.06327	-13.309	< 2e-16
Age30-39	-0.44170	0.05990	-7.373	1.66e-13
Age40-49	-0.90414	0.05386	-16.788	< 2e-16
Age50-59	-1.05926	0.05551	-19.082	< 2e-16
GenderM	0.12925	0.03422	3.777	0.000159
RaceHispa	-0.84163	0.06341	-13.272	< 2e-16
RaceWhite	-0.41177	0.05291	-7.783	7.08e-15
AlcohY	-0.87527	0.03822	-22.904	< 2e-16
ObeseY	-0.67870	0.03445	-19.701	< 2e-16
DiabetesY	-0.13673	0.05070	-2.697	0.007000
StrokeY	-0.18463	0.03734	-4.944	7.65e-07
DCD1: Yes	-2.25521	0.04688	-48.111	< 2e-16
Altcat1: 41-200	-0.51481	0.03494	-14.736	< 2e-16
Altcat2: 201-400	-1.00249	0.08017	-12.504	< 2e-16
Altcat3: >400	-2.25609	0.07138	-31.605	< 2e-16
Bilicat1: 1.2-2.5	-0.43682	0.03939	-11.090	< 2e-16
Bilicat2: 2.5-5	-1.08503	0.06776	-16.012	< 2e-16
Bilicat3: >5	-2.25948	0.12118	-18.646	< 2e-16
year	-0.04953	0.01005	-4.930	8.24e-07

Null deviance: 15548 on 8516 degrees of freedom

Residual deviance: 9696 on 8497 degrees of freedom

AIC: 13797

Waitlist Size

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	-428968	119538.5	-3.58854	0.022992
Year	220.5714	59.5756	3.702379	0.020792

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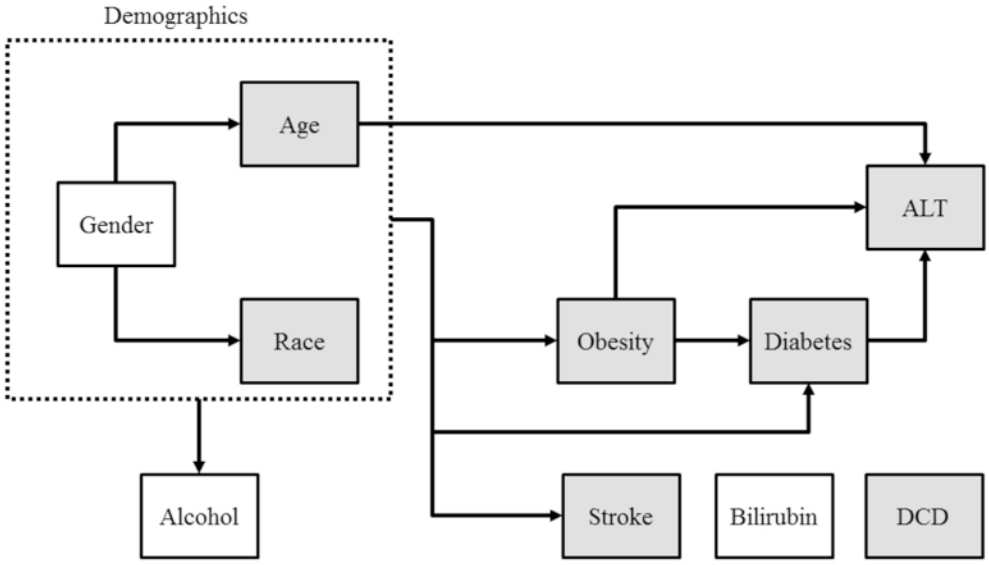

Figure 1. Structure and relationships between the simulation variables

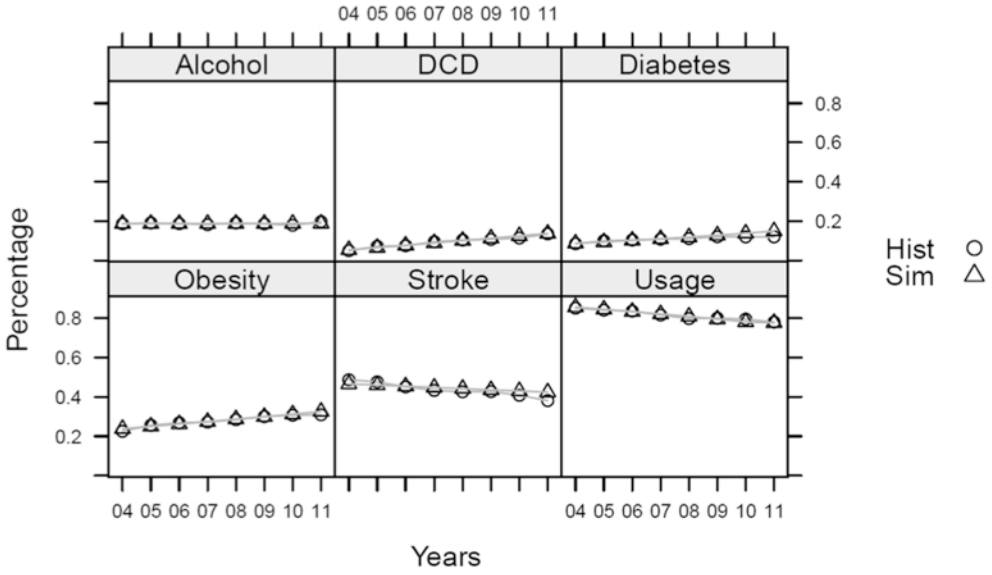

Figure 2. Simulated and historical values of 6 key variables between 2004 and 2011. The difference between these values was <1% in all cases

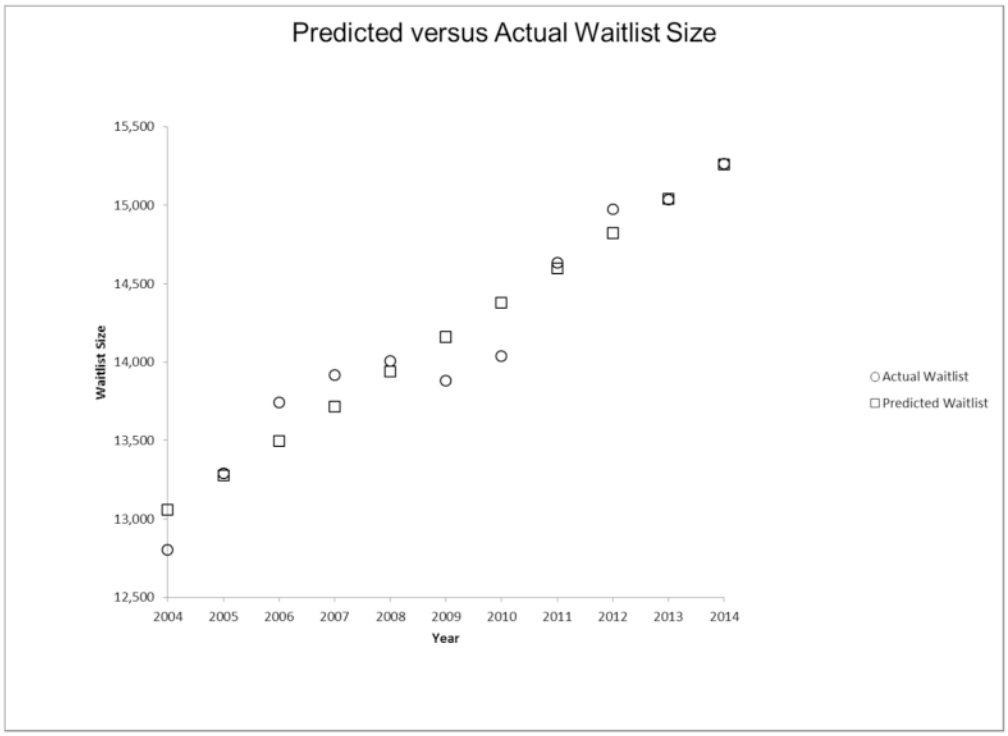

Figure 3. Forecasted and historical values of the number of adult LT waitlist candidates from 2004 through 2014

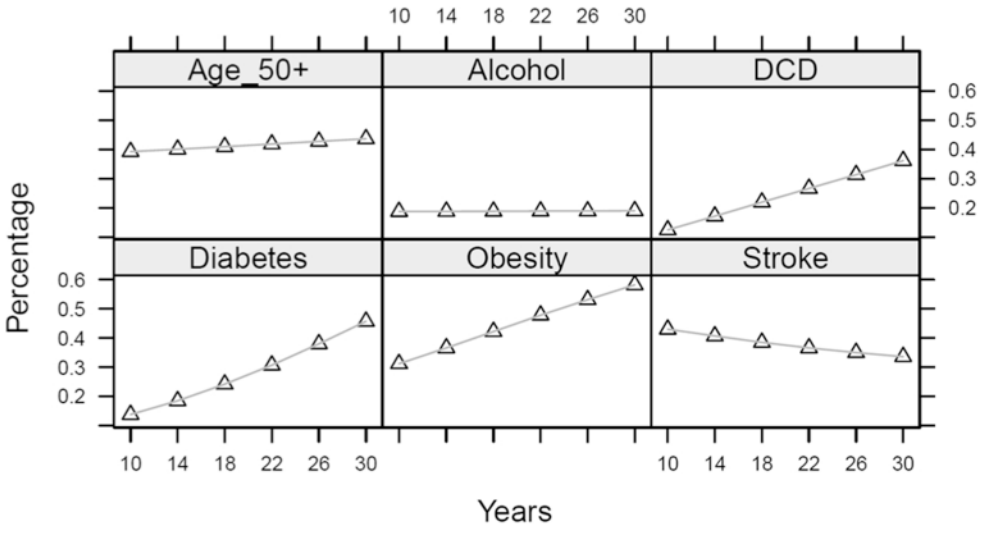

Figure 4. Simulated values of 6 key variables between 2010 and 2030

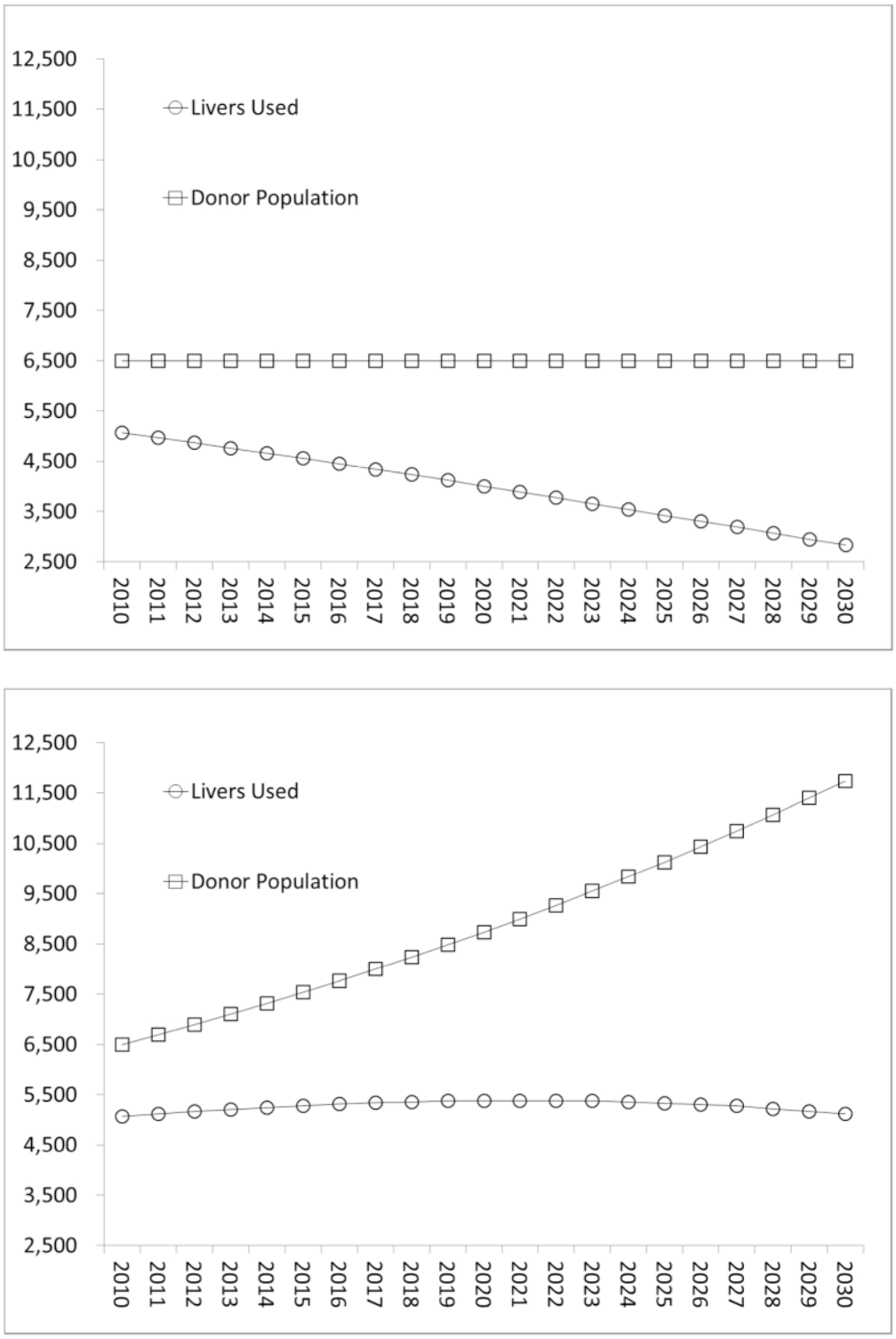

Figure 5. Projection of number of donors and number of livers used assuming that current trends remain in place -- (a) Donor Pool Remains Constant (b) Donor Pool Increases by 3% per year

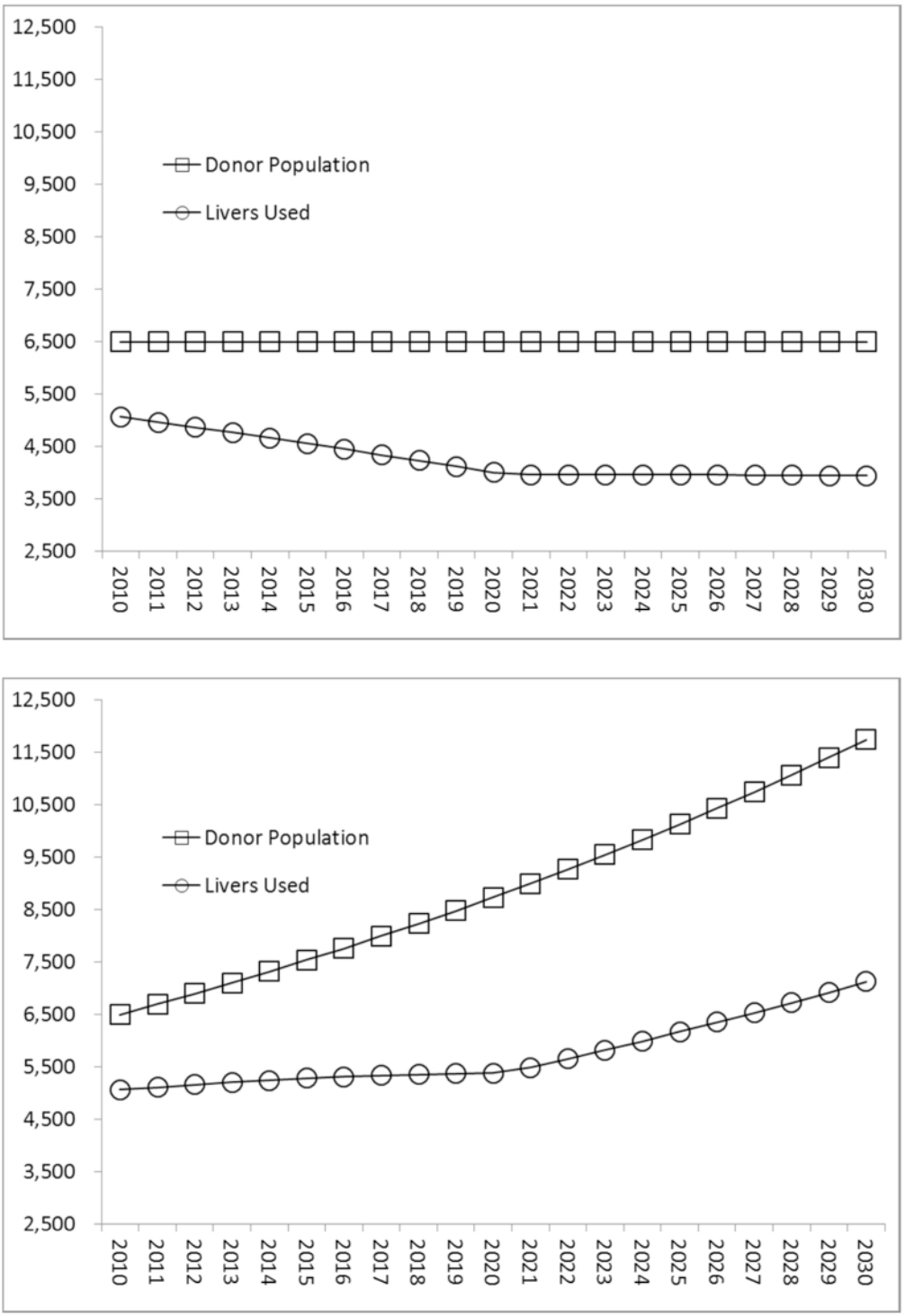

Figure 6. Projection of number of donors and number of livers used assuming changes in current trends -(a) Donor Pool Remains Constant (b) Donor Pool Increases by 3% per year

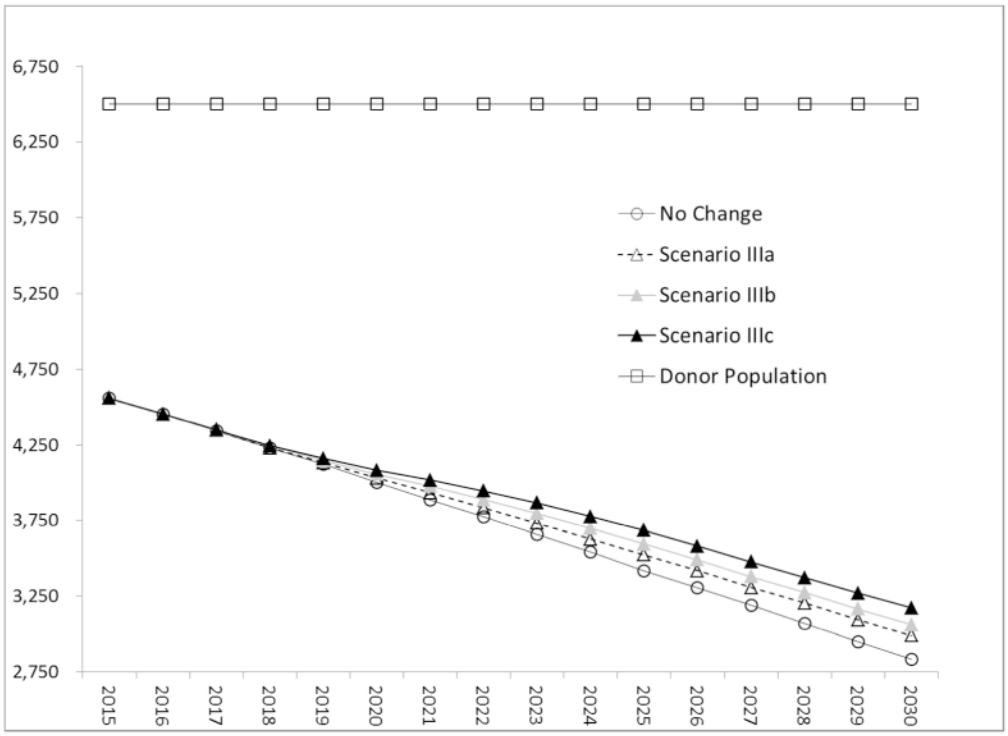

Figure 7. Projection of number of donors and number of livers if used reperfusion technology improves (Scenarios IIIa-IIIc) compared to Scenario I, when and donors remain constant

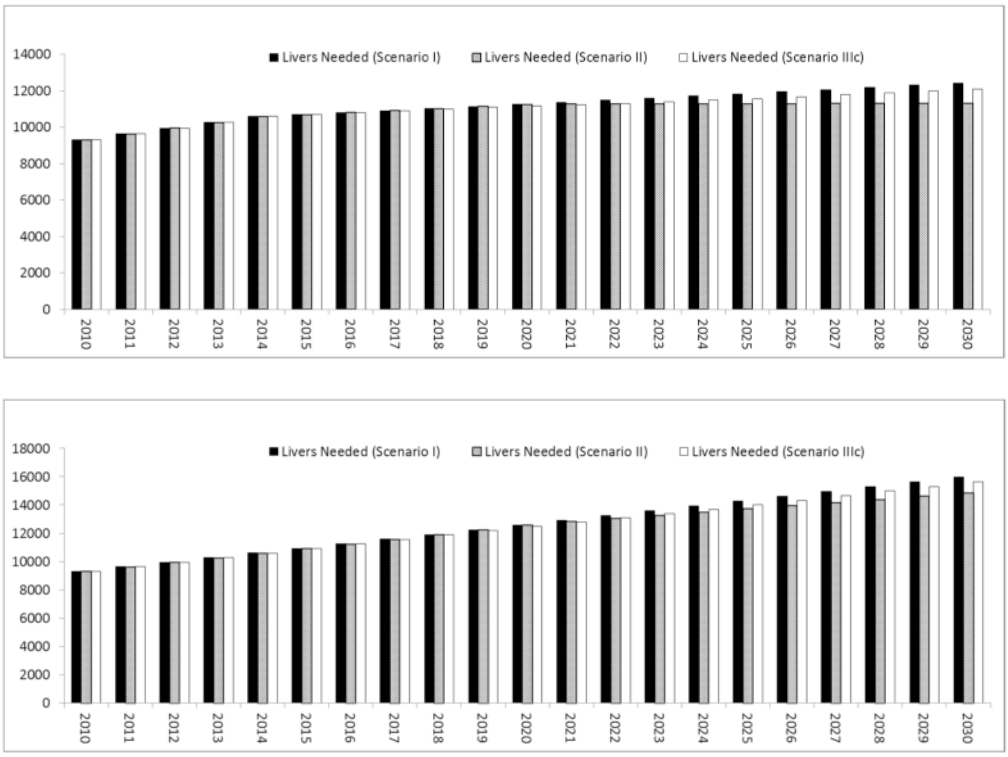

Figure 8. Prediction of gap between supply and demand for LTs, assuming the donor pool remains constant -- (a) Waitlist size remains constant after 2014 (b) Waitlist size grows as predicted

Table 1

Summary of statistical data processing

Independent Variable	Dependent Variables	Model
Gender	-	Constant Discrete Distribution
Age	Gender, Year	Linear Regression
Race	Gender, Year	Linear Regression
BMI (Obese) (Yes/No)	Gender, Age, Race, Year	Logistic Regression
Alcohol (Yes/No)	Gender, Age, Race	Logistic Regression
Diabetes (Yes/No)	Gender, Age, Race, Year, BMI	Logistic Regression
Stroke (Yes/No)	Gender, Age, Race, Year	Logistic Regression
Bilirubin	-	Constant Discrete Distribution
DCD (Yes/No)	Year	Linear Regression
ALT	Age, BMI, Diabetes, Year	Nested Logistic Regression
Liver Usage	Gender, Age, Race, BMI, Alcohol, ALT, Diabetes, Stroke, DCD, Bilirubin, Year	Logistic Regression

Table A1

ariables, 2004-2011. The difference shown is absolute difference

			Race								Bilirrubin					ALT				
49	**50-59**	**>=60**	**White**	**Black**	**Hispanic**	**%Alcoh**	**%Obese**	**%nObese**	**%Stroke**	**%Diabts**	**0: <=1.2**	**1: 1.2-2.5**	**2: 2.5-5**	**3: >5**	**%DCD**	**0: <=40**	**1: 41-200**	**2: 201-400**	**3: >400**	**%Use**
27	0.212	0.168	0.734	0.136	0.13	0.1873	0.238	0.762	0.466	0.087	0.737	0.21	0.04	0.013	0.054	0.604	0.335	0.031	0.03	0.856
27	0.216	0.166	0.725	0.142	0.133	0.1874	0.25	0.75	0.46	0.094	0.737	0.21	0.04	0.013	0.065	0.596	0.34	0.032	0.032	0.845
27	0.22	0.164	0.716	0.147	0.136	0.1874	0.262	0.738	0.454	0.102	0.737	0.21	0.041	0.013	0.077	0.587	0.345	0.034	0.034	0.833
27	0.224	0.163	0.708	0.153	0.14	0.1874	0.274	0.726	0.448	0.11	0.737	0.21	0.041	0.013	0.089	0.579	0.35	0.035	0.036	0.821
26	0.228	0.161	0.699	0.158	0.143	0.1875	0.287	0.713	0.442	0.119	0.737	0.21	0.041	0.013	0.101	0.571	0.355	0.036	0.038	0.809
26	0.231	0.159	0.69	0.164	0.146	0.1877	0.299	0.701	0.435	0.128	0.737	0.21	0.041	0.013	0.113	0.563	0.36	0.037	0.04	0.795
26	0.236	0.157	0.681	0.17	0.15	0.188	0.312	0.688	0.43	0.138	0.737	0.21	0.041	0.013	0.125	0.555	0.365	0.038	0.042	0.781
26	0.24	0.156	0.672	0.175	0.153	0.1884	0.326	0.674	0.424	0.149	0.737	0.209	0.041	0.013	0.137	0.546	0.37	0.04	0.044	0.766
25	0.243	0.154	0.663	0.181	0.156	0.1882	0.339	0.661	0.418	0.16	0.737	0.21	0.041	0.013	0.149	0.538	0.374	0.041	0.047	0.75
25	0.247	0.152	0.655	0.186	0.159	0.1884	0.353	0.647	0.412	0.172	0.737	0.209	0.041	0.013	0.161	0.53	0.378	0.042	0.05	0.734
25	0.251	0.15	0.646	0.192	0.163	0.1885	0.366	0.634	0.407	0.185	0.737	0.209	0.041	0.013	0.172	0.521	0.383	0.044	0.052	0.718
25	0.255	0.149	0.637	0.197	0.166	0.1888	0.38	0.62	0.401	0.199	0.737	0.209	0.041	0.013	0.184	0.512	0.387	0.045	0.055	0.7
24	0.259	0.147	0.629	0.203	0.169	0.1886	0.394	0.606	0.396	0.212	0.737	0.209	0.041	0.013	0.196	0.504	0.391	0.047	0.058	0.683
24	0.263	0.145	0.62	0.208	0.172	0.1885	0.408	0.592	0.39	0.227	0.737	0.209	0.041	0.013	0.208	0.496	0.395	0.048	0.061	0.664
23	0.267	0.143	0.611	0.214	0.175	0.1887	0.422	0.578	0.385	0.242	0.737	0.209	0.041	0.013	0.22	0.488	0.399	0.049	0.064	0.646
23	0.271	0.142	0.603	0.219	0.178	0.1889	0.436	0.564	0.38	0.257	0.737	0.209	0.041	0.013	0.231	0.479	0.403	0.051	0.068	0.627
23	0.275	0.14	0.594	0.225	0.181	0.1888	0.45	0.55	0.375	0.273	0.737	0.21	0.041	0.013	0.243	0.471	0.406	0.052	0.071	0.607
			Race								Bilirrubin					ALT				
49	50-59	>=60	White	Black	Hispanic	%Alcoh	%Obese	%nObese	%Stroke	%Diabts	0: <=1.2	1: 1.2-2.5	2: 2.5-5	3: >5	%DCD	0: <=40	1: 41-200	2: 201-400	3: >400	%Use
32	0.214	0.169	0.728	0.136	0.136	0.186	0.225	0.775	0.487	0.085	0.737	0.211	0.040	0.013	0.050	0.606	0.329	0.033	0.031	0.851
26	0.220	0.171	0.714	0.147	0.139	0.191	0.256	0.744	0.476	0.100	0.728	0.213	0.048	0.010	0.072	0.599	0.337	0.030	0.033	0.841
34	0.218	0.161	0.709	0.155	0.136	0.187	0.268	0.732	0.451	0.104	0.750	0.198	0.040	0.012	0.075	0.580	0.355	0.032	0.034	0.836
21	0.219	0.156	0.707	0.149	0.144	0.182	0.272	0.728	0.433	0.108	0.739	0.209	0.042	0.010	0.095	0.567	0.362	0.034	0.037	0.816
21	0.224	0.163	0.703	0.160	0.137	0.191	0.284	0.716	0.426	0.111	0.747	0.198	0.044	0.011	0.104	0.568	0.356	0.036	0.040	0.798
30	0.236	0.160	0.702	0.157	0.141	0.186	0.300	0.700	0.427	0.121	0.747	0.200	0.042	0.011	0.107	0.576	0.348	0.039	0.037	0.800
17	0.226	0.152	0.692	0.168	0.141	0.179	0.307	0.693	0.408	0.120	0.762	0.184	0.041	0.014	0.114	0.561	0.364	0.040	0.035	0.795

			Race							Bilirrubin				ALT			
	40-49	**50-59**	**>=60**	**White**	**Black**	**Hispanic**	**%Alcoh**	**%Obese**	**%nObese**	**%Stroke**	**%Diabts**	**0: <=1.2**	**1: 1.2-2.5**	**2: 2.5-5**	**3: >5**	**%DCD**	**0: <=40**	**1: 41-200**	**2: 201-400**	**3: >400**	**%Use**
	0.162	0.229	0.145	0.705	0.160	0.135	0.197	0.309	0.691	0.381	0.120	0.775	0.181	0.032	0.012	0.135	0.543	0.373	0.046	0.038	0.787
				Race								Bilirrubin					ALT				
	40-49	50-59	>=60	White	Black	Hispanic	%Alcoh	%Obese	%nObese	%Stroke	%Diabts	0: <=1.2	1: 1.2-2.5	2: 2.5-5	3: >5	%DCD	0: <=40	1: 41-200	2: 201-400	3: >400	%Use
	0.16%	0.20%	0.15%	0.55%	0.01%	0.57%	0.18%	1.29%	1.29%	2.06%	0.15%	0.04%	0.07%	0.05%	0.02%	0.42%	0.21%	0.56%	0.25%	0.11%	0.47%
	0.39%	0.39%	0.50%	1.10%	0.53%	0.57%	0.34%	0.58%	0.58%	1.56%	0.62%	0.87%	0.33%	0.83%	0.29%	0.70%	0.33%	0.27%	0.18%	0.12%	0.39%
	0.16%	0.20%	0.28%	0.73%	0.82%	0.01%	0.07%	0.60%	0.60%	0.35%	0.17%	1.30%	1.23%	0.10%	0.08%	0.18%	0.74%	0.95%	0.23%	0.01%	0.27%
	0.39%	0.49%	0.73%	0.08%	0.39%	0.38%	0.51%	0.15%	0.15%	1.54%	0.25%	0.19%	0.08%	0.12%	0.33%	0.57%	1.17%	1.17%	0.08%	0.09%	0.47%
	0.39%	0.39%	0.19%	0.38%	0.19%	0.56%	0.37%	0.28%	0.28%	1.62%	0.81%	1.00%	1.24%	0.32%	0.18%	0.26%	0.31%	0.08%	0.02%	0.21%	1.11%
	0.49%	0.48%	0.10%	1.20%	0.72%	0.48%	0.17%	0.07%	0.07%	0.80%	0.73%	0.98%	1.04%	0.14%	0.18%	0.61%	1.29%	1.21%	0.21%	0.29%	0.49%
	0.98%	0.98%	0.48%	1.09%	0.24%	0.95%	0.86%	0.51%	0.51%	2.19%	1.78%	2.47%	2.60%	0.03%	0.07%	1.14%	0.61%	0.13%	0.22%	0.70%	1.42%
	1.07%	1.07%	1.10%	3.30%	1.48%	1.82%	0.84%	1.65%	1.65%	4.33%	2.94%	3.78%	2.78%	0.88%	0.12%	0.25%	0.26%	0.27%	0.56%	0.57%	2.12%